Estimation of individual evoked potential by wavelet transform

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ESTIMATION OF INDIVIDUAL EVOKED POTENTIAL BY WAVELET TRANSFORM

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ABSTRACT
A new method to improve the signal-to-noise ratio of single evoked potentials (EP) measurements is presented, in which, contrary to previous methods, no a priori assumptions on the signal are necessary. This method is based on the wavelets decomposition of the individual signals. A statistical thresholding is applied on the coefficients of the decomposition: we estimate whether the mean value of the coefficients across trials and for each time point is significantly different from a random estimate. The performance of the method is evaluated against similar ones with simulations and the method is applied to real data

KEY WORDS
Multiresolution wavelet decomposition, evoked potential, EEG/MEG

1 Introduction

Our understanding of brain functioning is largely indebted to imagery techniques. Electro– and magnetoencephalographic (MEEG)[1] techniques provide an excellent temporal resolution allowing an investigation of brain functioning at a time scale as low as a millisecond, along with a fair spatial resolution[1, 2].

When analyzing MEEG recordings, one has to dissociate two types of activities: the so-called "evoked potentials", or "signal", induced by the brain activities related to specific events, and the background activity not related to the specific activity under investigation. Although the background activity (thereafter called "noise") can be of interest on some special cases, evoked potentials are the main activity of interest in MEEG, and the present work will concentrate on them. Note that, although, for sake of simplicity, we will call those activities "noise", they do not have the usual properties of "noise" in engineering literature. Indeed, since the main component of "noise" is the background brain activity, the "signal" and the "noise" are very similar in terms of frequencies, time course, sensitivity to brain changes etc..., making them particularly difficult to dissociate.

Evoked potentials are induced by the presentation of a stimulation, a preparation and/or execution of a motor act, or by internal information processing and represent transient electrical activities of some limited brain regions. Those evoked potentials are of small amplitude compared to noise: the signal/noise ratio (SNR) is typically around -10 dB. These two activities (evoked potential and background noise) are considered as additive and represented by an autoregressive (AR) model [3, 4]. Therefore, in order to study brain activities related to information processing in the brain, one has to "extract" the evoked potentials (signal) from the background activity (noise). The averaging procedure has long been used as the only technique to extract signal from noise. Depending on the signal to extract, one needs to average from 10 to 2000 repetitions of similar recordings.

The averaging procedure has several drawbacks, however. Both are related to the fact that one has to assume that the shape, the amplitude and the latency of the averaged activity is representative of the individual recordings. This is not necessarily true, however [5]. Another limitation comes from the fact that the inter-repetition variability is entirely lost in the averaging procedure, preventing, for example, correlation analysis with behavior and/or other physiological measures. Furthermore, recent advance in the coupling between EEG and fMRI are based on single trial estimate of EEG signal [6]. Thus, in order to improve our estimation of brain activity as recorded by MEEG, one needs to develop methods that do not rely on averaging techniques and that allow to estimate the parameters of the evoked potentials on a trial–by–trial basis.

To achieve this goal, two main directions have been followed: statistical techniques (like Principal Component Analysis – PCA, Independent Component Analysis – ICA, etc..., see [7] for an overview) and signal processing techniques. Here, we will focus on the later techniques.

In the signal processing approach, most of the techniques consider evoked potentials as stationary signal. The principle followed is a parametric approach [3, 4, 8].

Conventional approaches using numerical filtering have also been applied on the EEG traces to increase the signal/noise ratio [9, 10]. The frequency band is optimized following a spectral analysis of a sub-set of the averaged responses. The filters bank method, which combines the properties of the signal in both the time and the frequency domain in order to construct the "referent" signal has also been used to extract the individual signals [11]. To avoid

[1] Since EEG and MEG, have a lot in commun, we will use the acronym "MEEG" to refer to the two techniques

the assumption of stationarity, Quian-Quiroga [12] used wavelet transform to denoise the single sweep EEG signal and extract the P300 (a typical wave in EEG, see [13]) from noise. The **averaged** signal is decomposed into different scales (frequency bands) and times, by using the multiresolution wavelet transform [14]. In a second step, all the wavelets coefficients that do not correlate with the averaged signal are set to zero. The remaining coefficients describe the time-frequency plane in which the P300 wave is expected to occur. Those coefficients are applied to the single traces to keep only the time-frequency signature that corresponds to the P300. Although all those approaches have proved to be efficient and have provided useful information about single sweep activities, they are all, in a way or another, using the averaged signal as a template, either in the time or in the frequency domain, to estimate the single sweep activity. As indicated above, the averaged signal is not necessarily representative of the individual ones, however. Therefore, such a strategy of using the averaged trace as a template might not be fully appropriate to extract all the variability present in the single sweep activities.

Recently, Wang et al [15] proposed a method that avoids averaging. They used the method proposed by Donoho et al [16, 17] by applying a thresholding criterion in the wavelet domain. The signal is recovered from noisy data simply by setting to zero those wavelet coefficients below a certain threshold. It is to be noted that Wang et al. [15] applied this technique to so-called "Local Field Potentials", that is recordings performed within the brain, offering an excellent SNR ($\simeq$ 6 dB). This procedure is certainly not applicable for recovering the evoked potentials recorded in MEEG (*i.e.* recorded on the scalp) because, with those techniques, evoked potentials have a SNR around -10 dB.

Here we present a new method to denoise MEEG activities that avoids the use of any template and that makes no a priori assumptions regarding the properties of the signal, neither in the time nor in the frequency domain. In this aim, we used a well established property of the signal largely underused for this purpose: from trial to trial the signal (*i.e.*, the evoked potentials) is fairly stable in time with respect to the triggering events, whereas the noise (background MEEG) fluctuates independently from them. Therefore, the core of the proposed method is to estimate, at each time point, the between-trials stability of frequency components to keep only the stable ones to reconstruct the signal.

2 Wavelet transform

The principle underlying the wavelet transform is to describe the temporal evolution of a signal through different time scales, by providing information about the local regularity. The wavelet transform is based on a simple principle. Let's consider first a function not infinite in time and which can be non-zero over a short period of time. This function is called the analyzing wavelet. The wavelet transform consists of, at any given time position, dilating or compressing the analyzing wavelet by a scale factor, and to compute the product of the analyzing wavelet with the signal, for each value of the scale factor. The product is called the wavelet coefficient. The wavelet coefficient will be high if there is a match between the frequency of the analyzing wavelet and the signal to analyze. Thus, a short-lasting activity will be detected at a low scale factor, and inversely, a long-lasting activity will be detected at a large scale factor. The continuous wavelet transform (CWT) of a signal x is defined for each time $t \in \mathbb{R}$ as :

$$Wc = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} \psi\left(\frac{t-b}{a}\right) x(t)\, dt \qquad (1)$$

where ψ is the wavelet function, a is the scale factor and b is the time shift. The factor $\frac{1}{\sqrt{a}}$ was introduced to guarantee energy preservation.

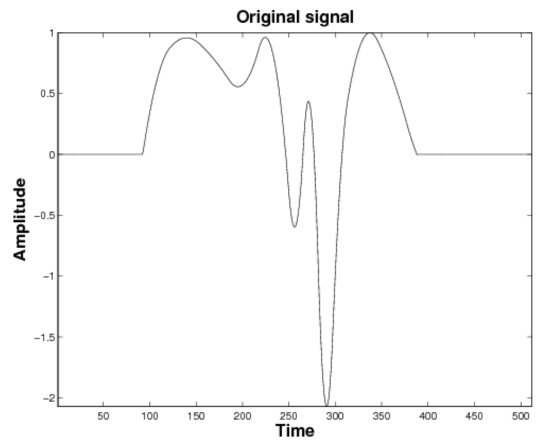

Figure 1. Original signal

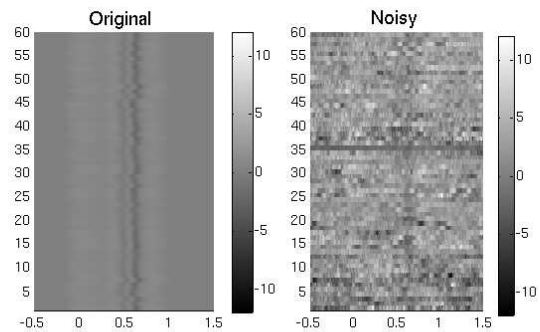

Figure 2. Original synthetic signals(a.) and noisy synthetic signals (b.), with a SNR=-10 dB

2.1 Multiresolution Wavelet Transform

The CWT is redundant and not efficient for algorithm implementations. To avoid redundancy and to increase the efficiency of algorithm implementations, the multiresolution wavelet transform (MWT) was introduced. It is based on the theory developed by Mallat [14], and is defined at discrete scales a and discrete times b by choosing the dyadic (basis 2) set of parameters $a = 2^j$ and $b = k2^j$, where $j \in \mathbb{Z}$ and $k \in \mathbb{Z}$ ($\mathbb{Z}$ being the integer set). This algorithm allows a fast decomposition of the signal at different scales, along with a reconstruction of the original signal. For the decomposition, this algorithm cascades a discrete filter and sub-samples the output. By low pass filtering and sub-sampling, we can obtain the approximation coefficients and by high pass filtering and sub-sampling, we obtain the detail coefficients. Basically, the reconstruction is the reverse process of decomposition.

3 Multi-trial denoising by WAvelet Statistical DEnoising (WASDE)

Denoising is the main application of MWT and is performed in both frequency **and** time domain, which is beyond the capacity of classical methods. The basic algorithm for denoising by MWT is simple and proceeds in three steps : 1) decomposition 2) thresholding of wavelet coefficients and 3) reconstruction of the denoised signal. The second step is the most important. The problem is to dissociate the coefficients representing the background activity (noise) from the coefficients of the evoked potentials (signal). The proposed method is based on the property of the orthogonal wavelet which compress the energy of the signal in a relative low number of large coefficients. On the contrary, the energy of the noise is spread across the whole transform and provides small coefficients. Thus, in the wavelets domain, signal and noise can be dissociated.

In typical MEEG experiments, several sweeps are recorded in the same conditions. Each sweep is decomposed in L detail levels ($D_1 \ldots D_L$) and the approximation A_L. L depends of the sampling rate (fs), with $fs = 2^{L+1}$. For example, for $fs = 256$ Hz, the number of decomposition is set to $L = 7$. For each decomposition level, the wavelet coefficients of all the sweeps are stored in a matrix whose horizontal rows represent the trials and each vertical row represents the successive time points. With $L = 7$, we obtain eight matrices ($D1, \ldots, D7, A7$).

For each level, the empirical distribution of coefficients is estimated by random permutation of the coefficients within each row (that is within each trial). For each permutation of the matrix, we compute the marginal mean values for each columns. One thus obtains the empirical distribution of the mean of the coefficients, and from there compute the inferior and the superior threshold corresponding to a confidence set at 0.05. The coefficients whose significance is below this confidence interval are retained while the other coefficients are set to zero. This thresholding is applied on the coefficients for each detail levels. One can then compute the inverse wavelet transform to obtain the denoised signal.

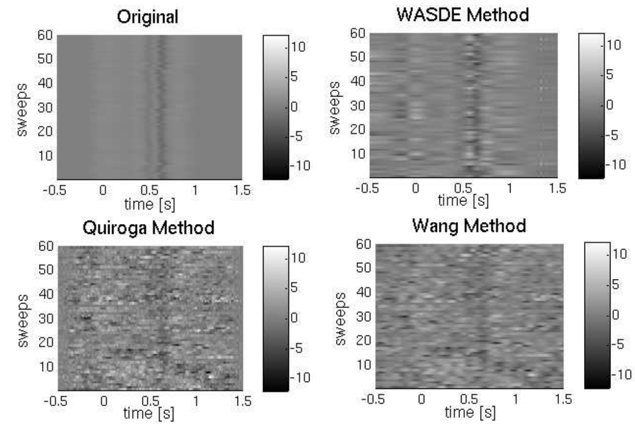

Figure 3. Comparison of three methods (Wasde, Guiroga and Wang), for a SNR = -10dB

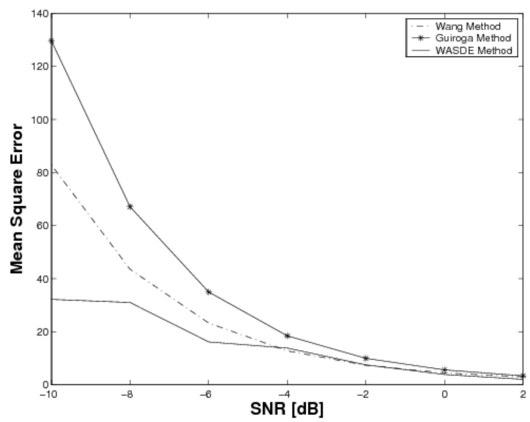

Figure 4. Mean square error for various SNR

4 Simulation

For the simulation, we built 60 synthetic traces of 512 points, composed of a series of waves (Fig. 1). The latency and the amplitude of those waves are varied to match the variability in latencies and amplitude of evoked potentials. EEG noise, whose level was scaled to alter the SNR between -10 dB and $+2$ dB, has been added to evoked potentials (Fig. 2). The analysing wavelet used in this simulation was a quadratic BSplines.

The three methods (Wasde, Guiroga and Wang) were fist compared for a SNR = -10 dB (Fig. 3). Visually, the Wasde method allows the best reconstruction of the original signal. To further the comparison between the three methods, we computed the mean square error, for SNR comprised between -10 dB and +2 dB. (Fig. 4). For low SNR (-10 dB $<$ SNR $<$ -4 dB), the Wasde method results in the lowest errors. For higher SNR (SNR $>$ -4 dB), Wang and Wasde give similar results (Fig. 4).

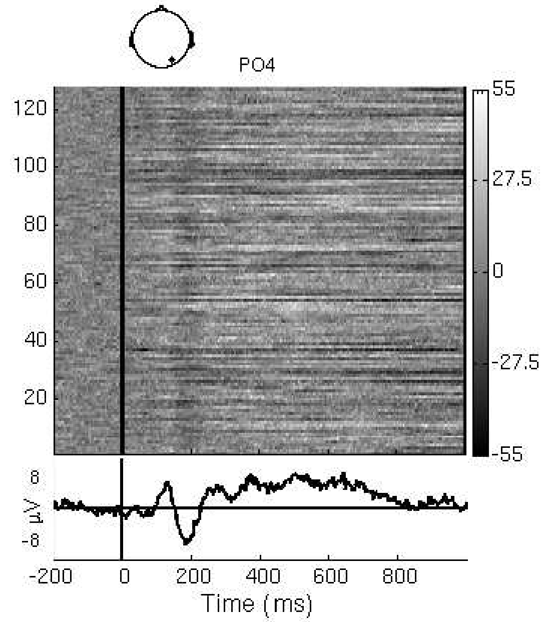

Figure 5. ERPs before denoising

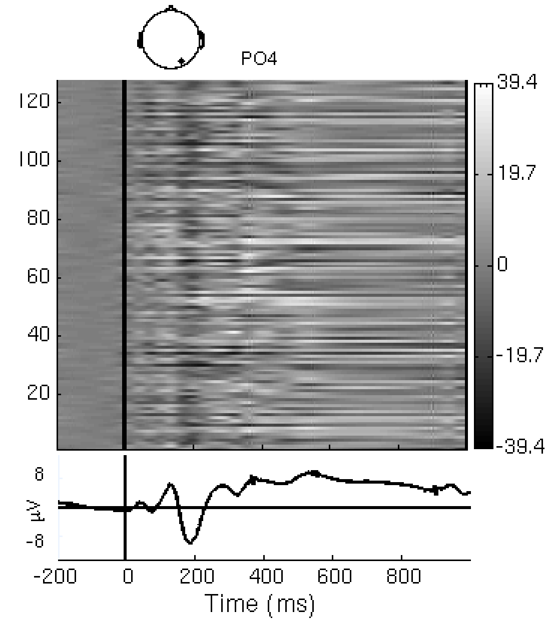

Figure 6. ERPs after denoising with Wasde method

5 Real data processing

The data were acquired with a 1024 Hz sampling frequency. Fig. 5 represents 125 trials. The X axis represents the time. At time 0, a visual stimulation was applied to the subject. The upper part of the Y axis represents the sweep number and lower part is the average value of the records. On the average, one can see on an evoked potential starting around 100 ms after stimulus presentation. However, on the individual sweeps, it is very difficult to extract the individual evoked potentials. Fig. 6 shows the same data after the denoising by the wasde method. First, one can see that the noise is removed before the apparition of the simulation. Second, on individual trials, on can now see the characteristics of the individual signals (Fig. 6).

6 Conclusions

We proposed a method to improve the SNR of an individual signal which can be applied without any a priori assumptions about the signal and the distribution of the wavelet coefficients. Comparison with recent methods by simulation and results obtained on real data has shown the efficiency of the proposed algorithm.

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